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Does Activity Engagement Protect Against Cognitive Decline in Old Age? Methodological and Analytical Considerations

Paolo Ghisletta,[1,2] Jean-François Bickel,[1] and Martin Lövdén[3]

[1]Center for Interdisciplinary Gerontology, University of Geneva, Switzerland.
[2]Faculty of Psychology and Educational Sciences, University of Geneva, Switzerland.
[3]Center of Lifespan Psychology, Max Planck Institute for Human Development, Berlin, Germany.

The literature about relationships between activity engagement and cognitive performance is abundant yet inconclusive. Some studies report that higher activity engagement leads to lower cognitive decline; others report no functional links, or that higher cognitive performance leads to less decline in activity engagement. We first discuss some methodological and analytical features that may contribute to the divergent findings. We then apply a longitudinal dynamic structural equation model to five repeated measurements of the Swiss Interdisciplinary Longitudinal Study on the Oldest Old. Performance on perceptual speed and verbal fluency tasks was analyzed in relation to six different activity composite scores. Results suggest that increased media and leisure activity engagement may lessen decline in perceptual speed, but not in verbal fluency or performance, whereas cognitive performance does not effect change in activity engagement.

IN RECENT years, a somewhat bewildering body of literature addressing the nature and magnitude of associations between various indicators of activity engagement on the one hand and various aspects of cognitive performance on the other hand has been accumulating. The results pertaining to the magnitude of and the potential causal relationships behind the associations are quite mixed at best, if not controversial (e.g., Hertzog, Hultsch, & Dixon, 1999; Hultsch, Hertzog, Small, & Dixon, 1999; Kramer, Bherer, Colcombe, Dong, & Greenough, 2004; Pushkar et al., 1999; Pushkar-Gold et al., 1995; Salthouse, Berish, & Miles. 2002). We believe that a number of methodological and analytical considerations might account for some of the divergence in extant results.

Methodological Considerations

Across existing empirical studies, theoretical definitions and subsequent operationalizations of activity engagement are highly variable. Whereas some studies focus on general activities (e.g., regular vs sporadic), others center on specific domains (e.g., cognitive, physical, or household). Moreover, studies that use an overall activity engagement or lifestyle index often differ in what exactly that index represents, how it was empirically obtained, and how the index is implemented in the analyses. Although there is probably greater consensus around the substantive meaning and the empirical measurement of particular cognitive performances, given the over one-century-old tradition of psychometrics, the definition and construction of activity scores seems more disputable. This gap calls for explicit definitions of the activity scores that are analyzed in empirical investigations.

Precise definitions of the analyzed activity scores further clarify the role of covariates that might or should have been included in the analyses. Indeed, the role of additional participants' information in the analyses may also be a source of disagreement across empirical examinations of activity–cognition relations (Hertzog et al., 1999; Mackinnon, Christensen, Hofer, Korten, & Jorm, 2003; Newson & Kemps, 2005). For example, gender and socioeconomic status may significantly affect not only the frequency of engagement in specific activities, but also cognitive performance. Thus, spurious relationships may emerge if these covariates are not accounted for. Furthermore, in samples of old and very old adults, knowledge about the participants' physiological functioning is essential. In particular, general health status as well as vision and hearing functioning may influence the likelihood of engaging in some activities, while at the same time it may correlate with cognitive performance for extraneous reasons (Lindenberger & Baltes, 1994). Not accounting for gender, socioeconomic status, health status, vision, and hearing may hence introduce spurious relations between activities and cognition, or it may confound the results.

Analytical Considerations

Even with the assumption that independent studies all agreed with respect to the methodological considerations outlined herein, and that the same underlying processes were in play, the results drawn from such studies may still vary as a function of the chosen analytical procedure. Indeed, the particular analytical strategy (i.e., statistical model) adopted is an often-cited reason for divergent results in this research field (e.g., Hertzog et al., 1999; Hultsch et al., 1999). Extant reports rely on various data-analytical techniques, including hierarchical multiple regression models that include change scores at the manifest, observed level (e.g., Newson & Kemps, 2005); latent longitudinal structural equation models (e.g., Pushkar-Gold et al., 1995); latent cross-lagged regression models (e.g., Aartsen, Smits, van Tilburg, Knipscheer, & Deeg, 2002); latent growth models (e.g., Mackinnon et al., 2003); and a particular structural equation model proposed by McArdle (2001) and McArdle and Hamagami (2001) called the Dual Change Score

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Model (applied in this context by Lövdén, Ghisletta, & Lindenberger, 2005). Although these analytical techniques may resemble each other to some extent, they come with different assumptions and features that are not always explicitly outlined and that may affect the interpretation of results.

Hierarchical multiple regression models attempt to estimate the amount of added predictability of chief variables over and above other variables of control. An example is provided by Newson and Kemps (2005), who predicted cognitive performance in various tasks (speed of processing, picture naming, incidental recall, and verbal fluency) at Time 1 as well as its change over 6 years, as a function of chronological age, general lifestyle (Adelaide Activities Profile; see Clark & Bond, 1995), and sensory functioning in a sample of nondemented older adults. Change in cognition was expressed as Time 2 scores residualized for Time 1 scores. Results revealed that general lifestyle was a unique predictor of all four baseline cognitive scores, as well as of change in speed of processing, picture naming, and incidental recall. The reciprocal relationship (the effect of baseline cognitive performance on baseline and change in activity engagement) was not investigated.

Latent longitudinal models are usually confirmatory factor models, in which variables thought to reflect the same underlying constructs are assessed at each occasion of measurement. This allows researchers to analyze change processes not just at the variable (manifest) level, but at the factor (latent) level. The main advantage of this methodology arises from defining change in latent, rather than in manifest, space, thereby removing unrelated sources of variance, which may seriously call into question the psychometric qualities of change scores obtained at the manifest level (Cronbach & Furby, 1970; but see also Collins, 1996, and Nesselroade & Cable, 1974). Pushkar-Gold and colleagues (1995) applied such a model to a sample of 316 Canadian veterans (age, $M = 64.75$) contacted about 40 years after World War II enrollment. The sample's archival enlistment data included, among others, a test of verbal and a test of nonverbal abilities. The veterans were readministered the two cognitive tests together with a habitual activities list (Arbuckle, Gold, & Andres, 1986), the Expectancy Locus of Control Scale (Reid & Ziegler, 1980), and a measure of socioeconomic status. Pushkar-Gold and colleagues defined a lifestyle factor with the three noncognitive scores and found that those veterans with higher initial verbal abilities, higher education level, and of upper socioeconomic class were more likely to develop an engaged lifestyle, which in turn alleviated decline in verbal abilities later in life. However, no relation between nonverbal abilities and lifestyle appeared. The effects of earlier lifestyle on change in cognition could not be investigated.

Latent cross-lagged regression models are similar to latent longitudinal models, but they presuppose that all variables have been assessed at two time points and that all earlier factor scores may influence later factor scores. These models define the same factors at two time points and regress the factors at Time 2 on those at Time 1. Of particular interest are the regression weights that each factor at Time 1 has on other factors at Time 2 over and above the autoregressions. Aartsen, Smits, van Tilburg, Knipscheer, & Deeg (2002) applied a series of bivariate latent cross-lagged regression models between one of three everyday activities (social, experiential, and developmental) and one of five cognitive functioning scores (the Mini-Mental State Examination, from Folstein, Folstein, & McHugh, 1975; immediate recall; learning; fluid intelligence; and information-processing speed). Their sample consisted of 2,076 participants (Time 1, age $M = 68.7$, $SD = 8.3$ years) of the Longitudinal Aging Study Amsterdam (Deeg, Knipscheer, & van Tilburg, et al., 1993), who were assessed twice. The results indicated that, over the 6-year period elapsed between the two waves, none of the three activities at Time 1 influenced any of the cognitive scores at Time 2. The only cognitive score that influenced engagement in an activity was information-processing speed, affecting developmental activities (i.e., following a course and engaging in outdoor sports), which suggests that participants with good cognitive functioning may prefer cognitively demanding activities. These models, however, do not explicitly define change, so that the understanding of the models' outcomes when two variables with differing change functions are analyzed is not intuitive, because they do not estimate the reciprocal influences in the presence of systematic change components (although change is usually implied, this model does not explicitly include its expectations). Moreover, psychometric properties of the variables (such as their reliabilities, i.e., amount of error variance, and stabilities, i.e., amount of true interindividual differences in change) may confound the results (e.g., Rogosa, 1980).

Latent growth models are typically applied to repeated measures over at least three occasions. In general, two factors are defined over the longitudinal assessment. The first is usually called the *level* or *intercept*, and it defines the reliable portion of the typical performance at a precise point in time (often, Occasion 1). The second factor is usually called the *change* or *slope*, and it defines the reliable, systematic long-term deviations around the level or intercept. The functional form of change is represented by the factorial loadings of the change factor on the repeated measurements. These loadings may either be fixed to known values in accordance with predefined mathematical functions (e.g., linear, quadratic, exponential, or Weibull) or estimated empirically. This model strategy offers a very flexible and useful analysis of change, because it explicitly models systematic change components. Mackinnon and associates (2003) adopted a latent growth modeling strategy to investigate the relationships between levels and changes of an overall activity composite score (including physical, rest, interest and hobby related, and planned activities) and cognitive performance (memory, speed, and crystallized intelligence) in a sample of 887 older adults, aged 70 years or older, who were assessed three times over 7 years. The researchers' main results were that an overall decrease in activity engagement correlated with deteriorations in all three cognitive domains and that, among those who participated during the whole study, individuals whose activity engagement remained stable experienced the same decrease on the three cognitive domains as individuals whose activity diminished. The authors concluded that activity engagement does not protect against cognitive decline. Furthermore, they specified that the direction of the possible causation between activities and cognition was not resolvable, because latent growth models examine concurrent associations between changes, and not lead–lag relations between variables.

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Motivated by the flexibility of latent growth models and by the desire to disentangle the directionality of influences within a given limited system of variables, McArdle and Hamagami (McArdle, 2001; McArdle & Hamagami, 2001; also see McArdle et al., 2004) developed the Dual Change Score Model (DCSM), which combines several features of the models just described. In particular, in a bivariate setting, the model contains the explicit and flexible definition of change inherent in latent growth models as well as, in conceptual analogy to the cross-lagged regression models, the inclusion of coupling effects of earlier measurements on later changes. The bivariate DCSM (BDCSM) explicitly separates true from error variance independently for the two variables of analysis, models the variables' systematic change around the intercept, and simultaneously includes competing hypotheses about lead–lag effects between the two variables. What makes the BDCSM special, however, is that it simultaneously estimates (a) the systematic change patterns of both variables, (b) each variable's autoproportional effect, and (c) the coupling effect that each variable may exert on the changes of the other variables. These coupling effects are not defined, as is the case for cross-lagged regression models, from Time 1 to Time 2 values, but from Time t values to the reliable portion of change occurring between times t and $t + \Delta t$, where Δt represents the time interval of analysis (usually set to 1 time unit). In other words, the explicit definition of change is an inherent, rather than inferred, part of the model, and each variable may affect its own as well as the other variable's change.

Lövdén, Ghisletta, and Lindenberger (2005) applied the BDCSM to three repeated measurements of the 516 adults (age, $M = 85.04$, $SD = 8.68$) of the Berlin Aging Study (P. B. Baltes & Mayer, 1999). Of particular interest were the longitudinal associations between a composite score of overall social participation (M. M. Baltes, Maas, Wilms, Borchelt, & Little, 1999) and one of perceptual speed. The main findings indicated that, over the 6-year period examined, both social participation and perceptual speed decreased and previous scores of social participation influenced subsequent changes in perceptual speed, whereas the opposite did not hold. On the basis of these dynamic (state affecting change) across-domain lead–lag effects, the authors concluded that, to a certain degree, an active lifestyle may alleviate decline in perceptual speed.

Objectives

In this study we intend to investigate further the relationships between engagement in various types of activities and performance in two cognitive domains in a sample of very old individuals. To address the methodological considerations outlined herein, we investigated six types of different activities in relation to performances in two cognitive abilities, while controlling for several potentially confounding covariates. In light of the analytical considerations discussed, we applied the BDCSM in 12 separate analyses (6 activity variables $\times$ 2 cognitive variables). We applied the DCSM in a bivariate fashion because (a) our theoretical motivation calls for the investigation of dynamic links between the two distinct domains of cognitive performance and activity engagement, and (b) because this facilitates substantive interpretations, in that with only two variables analyzed, lead–lag relations can be interpreted in a straightforward fashion. (Note, however, that multivariate DCSMs extend beyond the bivariate case. For quadrivariate applications, see, for instance, McArdle, Ferrer-Caja, Hamagami, & Woodcock, 2002, or Ghisletta & Lindenberger, 2005.)

Methods

Participants

The Swiss Interdisciplinary Longitudinal Study on the Oldest Old (SWILSO-O, Lalive d'Epinay, Pin, & Spini, 2001) is a multicohort interdisciplinary study on aging in the French-speaking region of Switzerland, and it involves sociology, social and cognitive psychology, social medicine, and econometrics. Two cohorts were assessed on an approximately yearly basis, the first for nine waves from 1994 to 2004, with 340 participants at inception, and the second for five waves from 1999 to 2004, initially with 377 participants. The starting samples of each cohort were stratified by sex and region (urban vs semiurban) and composed of community-dwelling participants between about 80 and 85 years of age. Several domains were assessed during the interviews (social, health-related, familial, professional, cognitive, etc.).

Because the cognitive measures were introduced in the SWILSO-O in 1999, we could only include the waves from that year onward. More specifically, our sample consisted of the fifth to the ninth wave of the first cohort and the first to the fifth wave of the second cohort (i.e., all waves during which the cohorts were assessed in parallel). Moreover, because the cognitive tasks were only administered to participants able to respond, we did not include participants for whom answers were obtained by a proxy. Because longitudinal selectivity effects in SWILSO-O are weak (Ghisletta & Spini, 2004) and cohort analyses revealed no cohort effects, we merged the two cohorts into a unique analysis.

Activity Engagement

Participants were asked with which frequency (everyday, at least once a week, at least once a month, at least once a year, never) they engaged in a total of 16 activities. Table 1 lists the activities organized by type.

We computed first an exploratory (or unrestricted) and then a confirmatory (or restricted) maximum likelihood factor analysis to simplify the activity space and to estimate composite activity scores. We specified the exploratory factor analysis with Promax rotation and the Kaiser–Guttman rule (i.e., one component for each eigenvalue > 1). We specified the confirmatory factor analysis according to the solution of the exploratory factor analysis: $\chi^2(N = 529,\ df = 39) = 45.72$, $p = .213$. (The factor analysis reported here considered the 16 activities as normally distributed and applied listwise deletion to handle incomplete data. We also computed exploratory factor analyses that applied full information maximum likelihood, or FIML, estimation to handle incomplete data or considered the 16 activities as categorical variables. All solutions converged to the factorial representation shown in Table 1.)

The final confirmatory factor solution was quite good: $\chi^2(N = 529,\ df = 87) = 248.43$, root mean square error of approximation (RMSEA) $= 0.051$, value for test of close fit of RMSEA, $p < .05 = 0.39$, standardized root mean residual $= 0.045$,